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‘Too Interconnected To Fail’ Financial Network of US CDS Market: Topological Fragility and Systemic Risk

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Abstract

A small segment of credit default swaps (CDS) on residential mortgage backed securities (RMBS) stand implicated in the 2007 financial crisis. The dominance of a few big players in the chains of insurance and reinsurance for CDS credit risk mitigation for banks’ assets has led to the idea of *too interconnected to fail (TITF)* resulting, as in the case of AIG, of a tax payer bailout. We provide an empirical reconstruction of the US CDS network based on the FDIC Call Reports for off balance sheet bank data for the 4th quarter in 2007 and 2008. The propagation of financial contagion in networks with dense clustering which reflects high concentration or localization of exposures between few participants will be identified as one that is *TITF*. Those that dominate in terms of network centrality and connectivity are called ‘super-spreaders’. Management of systemic risk from bank failure in uncorrelated random networks is different to those with clustering. As systemic risk of highly connected financial firms in the CDS (or any other)

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financial markets is not priced into their holding of capital and collateral, we design a super-spreader tax based on eigenvector centrality of the banks which can mitigate potential socialized losses.

Keywords: Credit Default Swaps, Financial Networks, Eigenvector Centrality, Financial contagion, Systemic Risk, Super-spreader tax

1. Introduction

The 2007 financial crisis which started as the US ‘sub-prime’ crisis, through a process of financial contagion led to the demise of major banks and also precipitated severe economic contraction the world over. Since 2008, tax payer bailout and socialization of losses in the financial system has transformed the banking crisis into a sovereign debt crisis in the Euro zone. In the 2002-2007 period, credit risk transfer (CRT) from bank balance sheets and the use of credit derivatives to insure against default risk of reference assets has involved big US banks and non-bank FIs in the credit derivatives market which is dominated by credit default swaps (CDS). This market has become a source of market expectations on the probability of default of the reference entity which since 2008 has increasingly included high CDS spreads on sovereigns and FIs. Banks are major protection buyers and sellers in this market and have become vulnerable as a result. Due to inherent structural weaknesses of the CDS market and also those factors arising from poor regulatory design, as will be explained, CDS which constitute up to 98% of credit derivatives have had a unique, endemic and pernicious role to play in the 2007 financial crisis. This paper will be concerned with modelling a specific weakness of CDS which is also well known for other modern risk sharing institutions involving over-the-counter (OTC) financial derivatives, and this pertains to the heavy concentration of derivatives activities among a few main participants.

The key elements of financial crises, the case of 2007 financial crisis being no exception, is the growth of innovations in private sector liquidity and leverage creation which are almost always collateralized by assets that are procyclically sensitive, viz. those that lose value with market downturns.²

²The use of procyclical RMBS assets as collateral for bank liabilities in asset backed commercial paper (ABCP) conduits in the repo market is given as a fundamental reason for the contraction of liquidity and the run on the repo markets in the 2007 crisis, Gorton

27 The specific institutional propagators of the 2007 crisis involved residential
28 mortgage backed securities (RMBS) which suffered substantial mark downs
29 with the collapse of US house prices.³ Then it was a case of risk sharing
30 arrangements that went badly wrong. This came about due to the role of CDS
31 in the CRT scheme of Basel II and its precursor in the US, the Joint Agencies
32 Rule 66 Federal Regulations 56914 and 59622 which became effective on
33 January 1, 2002. This occurred in the context of synthetic securitization and
34 of Collateralized Mortgage Obligations (CMO) which led to unsustainable
35 trends and to systemic risk. Both holders of the RMBS and CMO assets in
36 the banking sector and those servicing credit risk via the CDS market (cf.
37 American Insurance Group (AIG)) required tax-payer bailouts.⁴

38 The Basel II risk weighting scheme for CRT of assets on bank balance
39 sheets and its forerunner in the US which set out the capital treatment in the
40 Synthetic Collateralized Loan Obligations guidance published by the Office
41 of Comptroller of the Currency (OCC 99-43) for the 2002 Joint Agencies
42 Rule 66, stand implicated for turbo charging a process of leverage that in-
43 creased connectivity between depository institutions and as yet unregulated
44 non-depository financial intermediaries and derivatives markets. Under Basel
45 I since 1988, a standard 8% regulatory capital requirement applied to banks
46 with very few exceptions for the economic default risk of assets being held
47 by banks. In the run up to Basel II since 2004 and under the 2002 US Joint
48 Agencies Rule 66, the 50% risk weight which implied a capital charge of 4%

(2009). The loss of confidence arising from the uncertainty as to which bank is holding impaired RMBS assets that were non-traded, typically called a problem of asymmetric information, exacerbated the problem.

³See, Brunnermeier (2009), Stulz (2010), Ashcroft and Schuermann (2008) and Gorton and Metrich (2009). They, respectively, cover the unfolding phases of the crisis, the specific characteristics of credit derivatives, the features relevant to sub-prime securitization and the collateralized debt obligations.

⁴Kiff et al. (2009) place the size of increased collateral calls on AIG's CDS guarantees following its ratings downgrades at a relatively modest \$15 bn that it was unable to meet. While the current cost to the US tax payer of the AIG bailout stands at \$170 bn, the initial \$85 bn payment to AIG was geared toward honouring its CDS obligations to counterparties totalling over \$66.2 bn. These include payouts to Goldman Sachs (\$12.9 billion), Merrill Lynch (\$6.8 bn), Bank of America (\$5.2 bn), Citibank (\$2.3 bn) and Wachovia (\$1.5 bn). Foreign banks were also beneficiaries, including Société Générale and Deutsche Bank, which each received nearly \$12 bn; Barclays (\$8.5 bn); and UBS (\$5 bn). The following 15 March 2009 press release "AIG Discloses Counterparties to CDS, GIA and Securities Lending Transactions" provides useful information.

49 on residential mortgages could be reduced to a mere 1.6% through the process
 50 of synthetic securitization and external ratings which implied 5 times more
 51 leverage in the system.⁵ In synthetic securitization and CRT, an originating
 52 bank uses CDS or guarantees to transfer the credit risk, in whole or in part, of
 53 one or more underlying exposures to third-party protection providers. Thus,
 54 in synthetic securitization, the underlying exposures remain on the balance
 55 sheet of the originating bank, but the credit exposure of the originating bank
 56 is transferred to the protection provider or covered by collateral pledged by
 57 the protection provider. This strongly incentivized the use of CDS by banks
 58 which began to hold more MBS on their balance sheets and also brought
 59 AAA players such as AIG, hedge funds and erstwhile municipal bond insurers
 60 called Monolines into the CDS market as protection sellers.⁶ Only banks
 61 were subject to capital regulation while about 49% (see, British Bankers
 62 Association for 2006 for the breakdown of institutions involved as CDS pro-
 63 tection sellers and buyers) of those institutions which were CDS sellers in the
 64 form of thinly capitalized hedge funds and Monolines,⁷ were outside the reg-
 65 ulatory boundary. This introduced significant weakness to the CRT scheme
 66 leading to the criticism that the scheme was more akin to banks and other
 67 net beneficiaries of CDS purchasing insurance from passengers on the Ti-
 68 tanic. Indeed, a little known Monoline called ACA which failed to deliver
 69 on the CDS protection for RMBS held by Merrill Lynch is what finally led
 70 to its absorption by Bank of America.⁸ Further, as cited in the ECB CDS
 71 Report (ECB, 2009, p.57-58), in its 2007 SEC filing, AIG FP (the hedge

⁵The risk weight of 20% applies when a bank asset has CDS protection from an AAA rated guarantor.

⁶Acharya and Richardson (2010), Blundell-Wignall and Atkinson (2008), Hellwig (2010), Markose et al. (2010, 2012) have given detailed analyses of how the regulatory framework based on risk weighting of capital and CRT resulted in perverse incentives which left the financial system overleveraged and insolvent.

⁷At the end of 2007, AMBAC, MBIA and FSA accounted for 70% of the CDS contracts provided by Monolines with the first two accounting for \$625 bn and \$546 bn of this. The capital base of Monolines was approximately \$20 bn and their insurance guarantees are to the tune of \$2.3 tn implying leverage of 115.

⁸Standard and Poor Report of August 2008 states that Merrill Lynch had CDS cover from Monolines to the tune of \$18.8bn and of that ACA accounted for \$5bn. ACA, 29% of which was owned by Bear Stearns, along with other Monolines suffered a ratings downgrade in early 2008 and ACA demised in 2008 defaulting on its CDS obligations. ACA had \$69 bn of CDS obligations and only had \$425 million worth of capital.

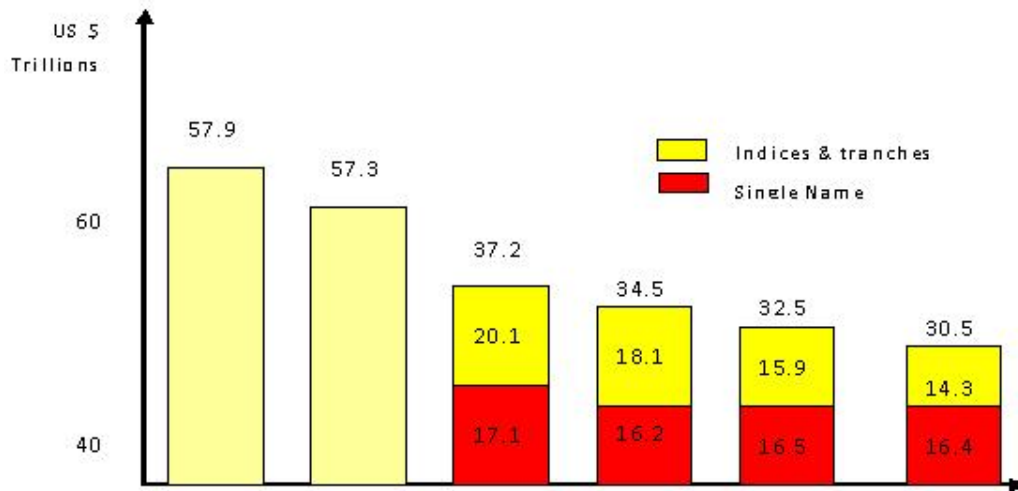


Figure 1: Credit Default Swaps Outstanding Gross Notional. Source: BIS December 07, June 08 which include all CDS contracts; DTCC for other dates record only 90% of CDS.

fund component of AIG) explicitly stated that it supplied CDS guarantees, in particular to European banks, in order for them to reduce capital requirements. The benefits that accrued to banks from CRT fell far short of the intended default risk mitigation objectives and as shown by Markose et al. (2012) participants of the CRT scheme were driven primarily by short term returns from the leveraged lending using CDS in synthetic CDOs as collateral in a carry trade.

Figure 1 shows how the CDS market peaked at about \$58 trillion in the run up to the 2007 crisis. In the post Lehman period the gross notional value⁹ of CDS has contracted due to the compression of CDS contracts with bilateral tear ups and a decline of CDS issuance. Tranche CDS shrank faster than single name CDS. During the short lived period of the CDO market for RMBS which peaked at over \$2 trillion in 2007, about \$1 trillion of the tranche based CDS was on sub-prime RMBS.

Undoubtedly, the main rationale behind CRT in the context of credit derivatives which led regulators to endorse these activities (see, e.g., IMF

⁹Following the DTCC, the CDS notional refers to the par value of the credit protection bought or sold. Gross notional value reported on a per trade basis is the sum of the CDS contracts bought (or equivalently sold) in aggregate.

88 (2002); OECD (2002); IAIS (2003); BIS (2004)) is that it allows financial
 89 intermediaries (FIs) to diversify away concentrated exposures on their bal-
 90 ance sheet by moving the risks to AAA rated institutions that seem better
 91 placed to deal with them. However, similar to the argument made by Darby
 92 (1994) about derivatives markets in general in their role in risk sharing, many
 93 have noted (see, Persuad (2002), Lucas et al. (2007), Das (2010) and Gibson
 94 (2007)) that the benefits of CRT will be compromised by the structural con-
 95 centration of the CDS market. Clearly, Basel II and III schemes for CRT¹⁰
 96 suffer from the fallacy of composition. The premise that the transfer of credit
 97 risk from banks' balance sheets, which is a good thing from the perspective
 98 of a bank especially as the capital savings incentives allow short run asset
 99 expansion, will also lead to diversification of risk does not follow at a collec-
 100 tive level. There is growing counterparty and systemic risk due to fragility in
 101 the network structures. Few have provided tools to quantitatively model and
 102 visualize the systemic risk consequences of what is called *too interconnected*
 103 *to fail (TITF)* that come with high concentration of CDS counterparties.¹¹
 104 Markose et al. (2012) has pointed out that the fallacy of composition type er-
 105 rors can be reduced with holistic visualization of the interconnections between
 106 counterparties using financial network models. The structural signature of
 107 such financial networks given by the heavy concentration of exposures needs
 108 to be modelled and analysed to understand the network stability properties
 109 and the way in which contagion propagates in the system. In view of the
 110 growing *structural* concentration in the provision of risk guarantees through
 111 financial derivatives, we claim the topological fragility of the modern risk
 112 sharing institutions is germane to issues on systemic risk.

113 Given the US centric nature of the CDS market for RMBS and the fact
 114 that the FDIC Call Reports comprehensively give data on gross notional,
 115 gross positive fair value (GPFV)¹² and gross negative fair value (GNFV) of

¹⁰Hellwig (2010) has correctly noted that as long as incentives for capital reduction are given for the use of CDS risk mitigants, it is business as usual in Basel III.

¹¹In the publicly available slides of a study by Cont et. al. (2009), Measuring Systemic Risk in Financial Networks cited in the 2009 ECB CDS Report (ECB, 2009), Cont et. al. simulate the CDS market network connectivity and exposure sizes on the basis of the empirical properties of the Brazilian and Austrian interbank markets. We maintain that the CDS market, especially as it affects US bank solvency, has considerably more clustering and concentration risk than interbank markets.

¹²The sum total of the fair values of contracts involves the money owed to a bank by its counterparties, without taking into account netting. This represents the maximum losses

116 CDS for all FDIC FIs, this paper will confine the CDS network model to
 117 fit the FDIC data set. Note, the activities of the FDIC financial firms are
 118 given in their capacity as national associations rather than in terms of global
 119 consolidated holdings. The number of US FDIC financial firms involved
 120 in CDS is very few ranging from between 26-38 or so in the period since
 121 2006 when this data has been reported. In 2006, we find that that top 5
 122 US banks (J.P. Morgan, Bank of America, Citibank, Morgan Stanley and
 123 Goldman Sachs) accounts for 95% of gross notional sell and over 97% in
 124 2007 of the total CDS gross notional sell of FDIC banks. In terms of the
 125 \$34 tn global gross notional value of CDS for 2008 Q4 given by BIS and
 126 DTCC, these top 5 US banks account for 92% of market share. Of the top
 127 100 SP-500 firms surveyed by Fitch in 2009 for derivatives use¹³, only 17 were
 128 found to be active in the CDS market and the top 5 US banks accounted for
 129 96% of CDS gross notional in 2009. While the network for CDS exposures
 130 for US banks in the 2007 Q4 period showed that Monolines and insurance
 131 companies were dominant as CDS protections sellers, by 2008 Q4 we have
 132 an even greater dominance of 5 US banks in the CDS market. This came
 133 about with the demise or merger of investment banks Bear Stearns, Lehman
 134 Brothers and Merrill Lynch, contraction of CDS activities by the Monolines
 135 and the nationalization of AIG. It is a sobering fact that the origins of the
 136 financial contagion as it emanated from CDS on RMBS on US banks' balance
 137 sheets accounts for only 13% of gross notional of total US bank holdings of
 138 CDS in 2006 Q1 and falling to 7% in 2007 Q2 (see Markose et al. (2012)).

139 This paper is concerned with characterizing the systemic risk from this
 140 class of derivatives by considering the topology of the financial network for
 141 counterparty exposures. Following the methods of the IBM project of MIDAS
 142 (see, Balakrishnan et al. (2010)) which aims to automate, access and visualize
 143 large financial datasets this paper will use the Markose et al. (2010) network
 144 'visualizer' for the CDS activities of FDIC firms. One of the objectives of the
 145 paper is to highlight the hierarchical core-periphery type structures within a

a bank could incur if all its counterparties default and there is no netting of contracts, and the bank holds no counter-party collateral. Fair values are market determined or model determined.

¹³The report by Fitch Ratings, 2009, "Derivatives: a Closer Look at What New Disclosures in the U.S. Reveal". The 100 companies reviewed were those with the highest levels of total outstanding debt in the S&P 1,500 universe. They represent approximately 75% of the total debt of S&P 1,500 companies.

146 highly sparse adjacency matrix to give a more precise depiction of financial
147 firms being *TITF* in that the highly connected financial firms will bring down
148 similarly connected financial firms implying large socialized loss of capital for
149 the system as a whole. It aims to give a more rigorous characterization in
150 terms of network statistics of extreme concentration of exposures between five
151 top US banks. We will highlight the high asymmetry in network connectivity
152 of the nodes and high clustering of the network involving a few central hub
153 banks (some-times called the ‘rich club’) which are broker-dealers in of the
154 CDS network.

155 By its nature of being a negative externality, systemic risk implications of
156 a bank’s connectivity and concentration of obligations are not factored into
157 the capital or collateral being held by banks. In a ratings based system, as
158 succinctly pointed out by Haldane (2009), leniency of capital and collateral
159 requirements for a few large highly rated FIs has resulted in excessive expan-
160 sion of credit and derivatives activities by them which is far beyond what can
161 be sustained in terms of system stability. Haldane (2009) calls such highly
162 interconnected financial intermediaries ‘super-spreaders’ and we will retain
163 this epithet in the financial network modelling that follows. Haldane (2009)
164 recommends that super-spreaders should have larger buffers. We design a
165 super-spreader tax based on eigenvector centrality of the nodes and we test
166 it for its efficacy to reduce potential socialized losses.

167 Section 2 gives a brief description of CDS and discusses the potential
168 systemic risk threats that arise from them. This includes the practice of
169 offsetting which creates dense connections between broker-dealers. In Section
170 3, we will briefly review the technical aspects of network theory and the
171 economics literature on financial networks. The main drawback of the pre
172 2007 economics literature on financial networks has been that models that
173 are based on empirical bilateral data between counterparties were few in
174 number to establish ‘stylized’ facts on network structures for the different
175 classes of financial products ranging from contingent claims and derivatives,
176 credit related interbank obligations and exposures and large value payment
177 and settlement systems. Where bilateral data on financial exposures is not
178 available, both empirical and theoretical models assumed network structures
179 to be either uncorrelated random ones (see, Nier et al. (2007)) or complete
180 network structures (see, Upper and Worms (2004)). As will be argued, these
181 approaches crucially do not have what we call the *TITF* characteristics.
182 While the stability of financial networks have been usually investigated using
183 the classic Furfine (2003) algorithm, sufficient emphasis has not been given

184 to the way in which contagion propagates in highly tiered and clustered
185 networks and stability of the system in terms of network characteristics has
186 not been studied. Section 4 discusses the necessary network stability results
187 and derives the super-spreader tax fund that can mitigate potential socialized
188 losses from the failure of highly connected banks. The super-spreader tax is
189 based on the eigenvector centrality of the FI in order to internalize the system
190 wide losses of capital that will occur by failure of big CDS broker-dealers.

191 In the empirical Section 5, a quantitative analysis leading to the empirical
192 reconstruction of the US CDS network based on the FDIC Q4 2007 and Q4
193 2008 data is given in order to conduct a series of stress tests that investi-
194 gate the consequences of the high concentration of activity of 5 US banks.
195 In 2007 Q4, non-bank FIs such as Monolines and hedge funds are found to
196 be dominant in terms of eigenvector centrality. In 2008 Q4, J.P. Morgan is
197 identified as the main super-spreader. The substantial threat to US banks
198 from non-US (mainly European) banks as net CDS sellers is also identified.
199 An equivalent uncorrelated random network equivalent in size, connectivity
200 and total GNFBV and GPFV for each bank is also constructed and systemic
201 risk from bank failure in uncorrelated random networks is shown to be dif-
202 ferent from the empirically calibrated CDS network. Results are provided
203 on how the super-spreader tax fund operates. Section 6 concludes the paper
204 and outlines future work.

205 **2. Over the Counter CDS Contracts: Potential Systemic Risk Threats**

206 *2.1. CDS Contract and Inherent Problems*

207 A single name credit default swap is a bilateral credit derivative contract
208 specified over a period, typically 5 years, with its payoffs linked to a credit
209 event such as default on debt, restructuring or bankruptcy of the underlying
210 corporate or government entity. The occurrence of such a credit event can
211 trigger the CDS insurance payment by the protection seller who is in receipt
212 of periodic premia from the protection buyer. Figure 2 sets out the structure
213 of a CDS contract.

214 Every over the counter (OTC) CDS contract is bilaterally and privately
215 negotiated and the respective counterparties and the contracts remain in
216 force till the maturity date. This raises problems with regard to counterparty
217 risk and also indicates why gross exposure matters. The periodic payments
218 of premia are based on the CDS spread and quoted as a percentage of the
219 gross notional value of the CDS at the start of the contract. The CDS

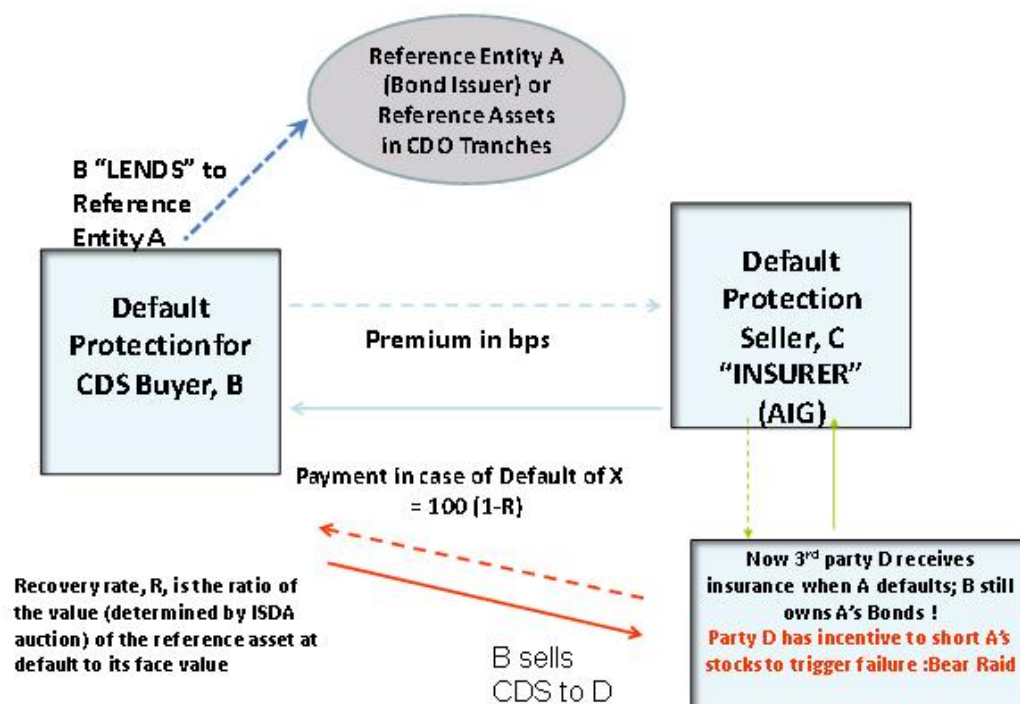


Figure 2: Credit Default Swap Structure, CDS Chain and Bear Raid. Note: Direction of CDS sale or protection guarantee is the unbroken arrow.

220 spreads being quoted fluctuate over time. As the payoff on a CDS contract
 221 is triggered by the default on debt, the CDS spread represents, in general,
 222 credit worthiness of the reference entity and specifically, the probability of
 223 default and the recovery value of the reference assets. All else being equal,
 224 higher spreads indicate growing market expectations of the default on the
 225 debt with a jump to default spike at the time of the credit event. Net CDS
 226 sellers and their counterparties holding impaired CDS reference assets may
 227 also find that CDS spreads on themselves as reference entities are adversely
 228 affected. This could hasten their own insolvency as liquidity risk in the form
 229 of the ability to raise funds is affected. This has been called ‘wrong way
 230 risk’. The 2009 ECB CDS report estimated this as the correlation in the
 231 CDS spreads of CDS sellers and their respective reference entities, and finds
 232 this has grown for sellers of CDS which rely on government bailout and then
 233 sell CDS with their respective sovereigns as reference entities. Circularity of
 234 risk arises from the fact that as noted by the DTCC in December 2008, 7 top
 235 dealers are themselves among the 10 top reference entities by net protection
 236 amounts.¹⁴

237 Hence, CDS spreads have strong self-reflexive properties in that they do
 238 not merely reflect the financial state of the underlying obligor, they can
 239 in turn accelerate the default event as ratings downgrade follow, cost of
 240 capital rises and stock market valuation falls for the obligor as the CDS
 241 spreads on them increase. These systemic risk factors are hard to model in
 242 formulaic CDS pricing models and hence such counterparty and circular risk
 243 are typically not modelled in CDS pricing models.

244 The controversial aspect about a CDS that makes the analogy with an
 245 insurance contract of limited use is that the buyer of a CDS need not own any
 246 underlying security or have any credit exposure to the reference entity that
 247 needs to be hedged. The so called naked CDS buy position is, therefore, a
 248 speculative one undertaken for pecuniary gain from either the cash settlement
 249 in the event of a default or a chance to offset the CDS purchase with a sale at
 250 an improved CDS spread. This implies that gross CDS notional values can
 251 be several (5-10) multiples of the underlying value of the debt obligations of

¹⁴In December 2008, the DTCC lists the following financial reference entities by net protection amounts: GE Capital (\$11.074 bn), Deutsche Bank (\$7.163 bn), Bank of America (\$6.797 bn), Morgan Stanley (\$6.318 bn), Goldman Sachs (\$5.211 bn), Merrill Lynch (\$5.211 bn), Berkshire Hathaway (\$4.632 bn), Barclays Bank (\$4.358 bn), UBS(\$4.311 bn), RBS(\$4.271 bn).

the reference entity. It has been widely noted that naked CDS buyers with no insurable interest will gain considerably from the bankruptcy of the reference entity. Note the ‘bear raid’ in Figure 2 refers to the possibility that when the CDS protection cover on a reference entity has been sold on to a third party, here D, who does not own the bonds of the reference entity, D has an incentive to short the stock of the reference entity to trigger its insolvency in order to collect the insurance to be paid up on the CDS. A naked CDS buy position is equivalent to shorting the reference bonds without the problems of a short squeeze that raises the recovery value of the bonds (and lowers the payoff on the CDS) when short sellers of the bonds have to ‘buy back’ at time of the credit event. Hence, naked CDS buying is combined with shorting stock of the reference entity. There is also the case that even those CDS buyers who have exposure to the default risk on the debt of the reference entity may find it more lucrative to cash in on the protection payment on the CDS with the bankruptcy of the reference entity rather than continue holding its debt. This is called the empty creditor phenomenon (see, Bolton and Oehmke (2011)).

Finally, as noted by Duffie et al. (2010) and as what happened in the case of the Bear Stearns hedge funds that had large CMO holdings, is that there can be a ‘run’ on the collateral posted by large CDS protection sellers if they suffer an actual or potential ratings downgrade. Counterparty credit risk rises to the level of systemic risk when the failure of a market participant with an extremely large derivatives portfolio can trigger large losses on its counterparties, which accelerates their failure. This can be accompanied by fire sales of the collateral which can lead to significant price volatility or price distortions. Those CDS contracts operating on the ISDA (International Swaps and Derivatives Association) rules also have a provision of cross-default. If a counterparty cannot post collateral in a specified time frame, it can deem to have defaulted and if the shortfall of collateral exceeds a threshold, the counterparty is deemed to have defaulted across other ISDA CDS. These cross-defaults (a potential situation that AIG was in) can trigger a domino effect as all parties close out. Attempts at novating CDS contracts guaranteed by the ‘closed out’ firm especially when the underlying is potentially devalued (as in the case of RMBS assets) with other protection sellers may be difficult and if successful it increases market concentration and network fragility as now there are fewer CDS protection sellers.

2.2. Broker-Dealer Concentration

The main strategy adopted by CDS dealers and counterparties to manage liquidity requirements is a practice called “offsets” which though individually rational may collectively contribute to systemic risk as the chains of CDS obligations increase and also merge. Offsets involve a strategy by which CDS participants can maximize revenue from spread trades and minimize collateral and final payouts. In Figure 2, for example, B having bought CDS cover from C, finds that the spreads have increased and may choose to eschew its hedge on the bonds of the reference entity A to earn the difference between the premia it pays to C and the higher premia it can now charge by an offset sale of CDS to D. This is marked by the red arrows in Figure 2 and is a typical spread trade. In this system, the ultimate beneficiary of CDS cover, in case of default of reference entity A, is the naked CDS buyer D. Assuming par value of \$10m for each CDS contract and zero recovery rate on reference entity bonds in Figure 2, note in the above scenario, C has an obligation to settle \$10m and then B’s obligations net to zero having settled with D. We will call this an open chain or tree.

Consider the case that C offsets with D (ie. the green arrows in Figure 2 are active). We now have a closed chain of reflexive obligations (B sells to D, D sells to C and C sells to B) with the gross notional CDS value at \$30m. Should the reference entity A default, then at settlement, if *all* parties in the CDS chain remain solvent (note that B has eschewed its hedge on the reference entity), aggregate/multilateral net CDS payouts for B, C and D are zero. Zero net notional CDS value¹⁵ gives nobody any non-premia related benefits, least of all cover on the reference entity bonds. If, however, any one of the counterparties fails, say C in a double default with the reference entity A, in the closed chain of CDS obligations, the whole chain may be brought down as B now has to face its obligation to D in terms of its gross amount

¹⁵We use the DTCC definition of aggregate net notional for each reference entity, ie. the sum of net protection bought by net buyers (or net protection sold by net sellers). See, <http://www.dtcc.com/products/derivserv/data/>. This is calculated at the level of each CDS market participant and based on the gross notional of buy and sell CDS contracts, separately aggregated over all counterparties, every participant is deemed a net buyer or net seller. The net buyers (or net sellers) values are summed up to get the aggregate net notional. Note also, this assumes zero recovery rate at time of settlement. This definition of net notional involves multilateral netting while reduction of counterparty risk can arise only from what can be bilaterally netted and nullified by mutual tear ups with the failed counterparty.

316 of \$10 m.

317 Bilateral offsets and a reflexive closed chain configuration provide the
318 most efficient *ex ante* net settlement liquidity requirements¹⁶ *if* all coun-
319 terparties deliver. Bilateral offsets on the same reference entity will reduce
320 collateral requirements and also counterparty risk as there will be mutual tear
321 ups when the counterparty fails. This is characteristic of network linkages in
322 inter-dealer relationships (Bliss and Kaufman, 2006). It must be noted that
323 extensive non-bilateral offsets, described above, using spread trades that aim
324 to maximize income from CDS spreads is essential for the price discovery
325 process. It will reduce aggregate net notional but not counterparty risk as
326 non-bilateral offsets will result in clustered interconnections and a high level
327 of systemic risk. Also, reduction in aggregate net notional comes at a price of
328 reducing the aggregate capacity of the CDS market to deliver hedge benefits
329 on reference assets.

330 In summary, the network topology which favours concentration of netted
331 flows between broker-dealers is efficient in regard to liquidity and collateral
332 requirements. However, it can be less stable than the one that requires more
333 *ex ante* net liquidity or collateral. Liquidity or collateral provision driven
334 from the vantage of individually rational calculations will fall short of the
335 amounts needed for system stability (see also footnote 15). The process of
336 offsets can nullify gross obligations if the reference entity defaults, but this
337 requires that net CDS sellers settle. Inability to do so, can make net CDS
338 sellers the main propagators of the financial contagion.¹⁷ The network struc-
339 ture, where key CDS net sellers with large market shares have heavy CDS
340 activity on them as reference entities, will show up as highly interconnected
341 linkages amongst these same players. This highly interconnected multi-hub

¹⁶Galbiati and Giansante (2010) have also find that networks that achieve economies in liquidity to be posted for settlement have reciprocal bilateral structures and also high interconnectivity in the form of clustering among key participants which facilitates efficient netting. Duffie and Zhu (2009) are somewhat misleading about the role of bilateral netting in the stability of the CDS market. They emphasize the savings in liquidity but, as they acknowledge, their model does not deal with so called “knock-on effects”, or the problem of how the default of one CDS counterparty can lead to a chain reaction affecting others.

¹⁷The 2009 ECB report on CDS indicates how the potential threat from AIG was not properly identified as the Fitch survey ranked AIG as only the 20th largest in terms of gross CDS obligations and failed to note that AIG was primarily a one way seller and its net CDS sell positions at \$372 bn was double the net notional amount sold by all DTCC dealers combined in October 2008.

like structure that characterizes inter-dealer CDS obligations will feature in the empirically determined CDS network model we develop.

3. Financial Network Analysis

Networks are defined by a pair of sets (N, E) which stand for nodes $N = 1, 2, 3, \dots, n$, and E is a set of edges. In financial networks, nodes stand for financial entities such as banks, other financial intermediaries and their non-financial customers. The edges or connective links represent contractual flows of liquidity and/or obligations to make payments and receive payments. Let i and j be two members of the set N . When a direct link originates with i and ends with j , viz. an out degree for i , we say that it represents payments for which i is the guarantor. Note, an agent's out degrees corresponding to the number of its immediate neighbours is denoted by k_i . In degrees represent receivables from the bank j to the bank i . In a system of linkages modelled by undirected graphs, the relationships between N agents when viewed in $N \times N$ matrix form will produce a symmetric matrix as a link between two agents will produce the same outcome whichever of the two partners initiated it. In contrast, directed graphs are useful to study relative asymmetries and imbalances in link formation and their weights.

3.1. Bilateral Flow Matrices

3.1.1. Adjacency Matrix and Gross Flow Matrix For CDS

Key to the network topology is the bilateral relations between agents and is given by the adjacency matrix. Denote the $(N + 1) \times (N + 1)$ adjacency matrix $A = (a_{ij})^I$, here I is the indicator function with $a_{ij} = 1$ if there is a link between i and j and $a_{ij} = 0$, if not. The N^{th} agent will be represented by the US non-bank sector such as Monolines, hedge funds and insurance companies. The $N + 1^{th}$ agent represents the non-US participants. This is also used to balance the system. The adjacency matrix becomes the gross flow matrix X such that x_{ij} represents the flow of gross financial obligations from the protection seller (the row bank) to the protection buyer j (the column bank). The FDIC Call Report Data gives the Gross Negative Fair Value (GNFV) for payables and Gross Positive Fair Value (GPFV) for receivables on all CDS products that a firm is involved in with all of its counterparties. Note GNFV and GPFV is a fraction (typically by a factor of 10) of the gross notional for which the firm is a CDS seller or buyer, respectively. The total gross payables in terms of GNFV for bank i is the sum over j columns or

377 counterparties, $G_i = \sum_j x_{ij}$ while the total gross receivables or total GPFV
 378 for each i is the sum taken across the i rows $B_i = \sum_i x_{ij}$. This is shown
 379 below :

$$\begin{array}{c}
 \mathbf{X} = \left[\begin{array}{cccccc}
 0 & x_{12} & x_{13} & \dots x_{1N} & \dots & x_{1N+1} \\
 x_{21} & 0 & x_{23} & \dots & \dots & x_{2N+1} \\
 . & . & 0 & \dots & \dots & . \\
 x_{i1} & . & . & 0 & & x_{iN+1} \\
 . & . & . & & 0 & \\
 x_{N+11} & . & . & x_{N+1j} & \dots & 0
 \end{array} \right] \left| \begin{array}{l}
 \Gamma = \sum_i G_i \\
 G_1 \\
 G_2 \\
 . \\
 G_i \\
 . \\
 G_{N+1}
 \end{array} \right. \\
 \\
 \Phi = \sum_j B_j \quad B_1 \quad . \quad . \quad B_j \quad \dots \quad B_{N+1}
 \end{array} \tag{1}$$

380 The zeros along the diagonal imply that banks do not lend to themselves
 381 (see, Upper, 2007) or in this case of CDS, provide protection to themselves.
 382 There can be asymmetry of entries such that for instance G_1 need not equal
 383 B_1 . However, aggregate GNFV including that of the $N + 1$ entity $\Gamma = \sum_i G_i$
 384 will be made to balance with $\Phi = \sum_j B_j$.

385 3.1.2. Bilaterally Netted Matrix of Payables and Receivables

386 Consider a matrix M with entries $(x_{ij} - x_{ji})$ gives the netted position
 387 between banks i and j . For each bank i the positive entries, $m_{ij} > 0$, in row
 388 i give the net payables vis-à-vis bank j and the sum of positive entries for
 389 bank i is its total bilaterally netted payables across all counterparties. This
 390 can be called i 's CDS liabilities. The sum of the negative entries, $m_{ij} < 0$,
 391 for each bank i in the i th row gives its total bilaterally netted receivables,
 392 which is often called CDS assets.¹⁸ Note the matrix M is skew symmetric

¹⁸Note, FDIC Call Reports give the derivatives assets (liabilities) which is the GPFV (GNFV) bilaterally netted by counterparty and product and also adjusted for collateral for each bank. However, this is reported in aggregate for all derivatives products and there is no publicly available bilaterally netted data on a bank's assets and liabilities for CDS. Hence, what we will take the i^{th} bank's CDS assets and liabilities to be the sum of the

393 with entries $m_{ij} = -m_{ji}$. To analyse the dynamics of the cascade of failure of
 394 the i th bank on the j th one, the matrix that is relevant will only contain the
 395 positive elements of the M matrix. The direction of the contagion follows
 396 from the failed bank i owing its counterparty j more than what j owes i .
 397 Further, as we will discuss in the next section, it is customary for the net
 398 exposures of bank j to bank i relative to j 's initial capital at time t , C_{j0} , to
 399 be greater than a threshold (signifying a proportion of j 's capital) before j
 400 is said to have failed. The matrix Θ that is crucial for the contagion analysis
 401 will have elements given as follows:

$$\Theta = \begin{bmatrix} 0 & \frac{(x_{12} - x_{21})^+}{C_{20}} & \frac{(x_{13} - x_{31})^+}{C_{30}} & .0. & & 0 \\ 0 & 0 & \frac{(x_{23} - x_{32})^+}{C_{30}} & & & \frac{(x_{3N} - x_{N3})^+}{C_{N0}} \\ \frac{(x_{1i} - x_{i1})^+}{C_{10}} & . & 0 & & & . \\ \frac{(x_{1N} - x_{N1})^+}{C_{10}} & . & ... & 0 & ... & \frac{(x_{iN} - x_{Ni})^+}{C_{N0}} \\ \frac{(x_{N1} - x_{1N})^+}{C_{10}} & . & ... & \frac{(x_{Nj} - x_{jN})^+}{C_{j0}} & 0 & . \\ \frac{(x_{Nj} - x_{jN})^+}{C_{j0}} & . & ... & \frac{(x_{Nj} - x_{jN})^+}{C_{j0}} & ... & 0 \end{bmatrix} \quad (2)$$

402 3.2. Topology of Financial Networks: Complete, Random and Uncorrelated, 403 Correlated and Small World

404 Like many real world networks, namely, socio-economic, communication
 405 and information networks such as the www, financial networks are far from
 406 random and uncorrelated. In order to construct a network for the US CDS
 407 market which shows dominance of few players with a 92% and upwards of
 408 concentration of CDS exposures, we will use what are referred to as small
 409 world networks¹⁹ (Watts (1999) and Watts and Strogatz (1998)). These
 410 networks have a top tier multi-hub of few agents who are highly connected
 411 among themselves (often called rich club dynamics) and to other nodes who

bilaterally netted positive amounts $\sum_j (x_{ij} - x_{ji})^+$ and the sum of the bilaterally netted negative amounts $\sum_j (x_{ij} - x_{ji})^-$, respectively.

¹⁹This is named after the work of the sociologist Stanley Milgram (Milgram, 1967) on the six degrees of separation in social networks. It has been found that globally on average everybody is linked to everybody else in a communication type network by no more than six indirect links.

show few if any connections to others in the periphery. The properties of small world networks and how contagion propagates through them will be briefly contrasted with that for the uncorrelated Erdős-Renyi random graph and also the Barabási and Albert (1999) scale free networks.

Networks are mainly characterized by the following network statistics (a) Connectivity of a network is given by the number of connected links divided by the total number of links. There are $N(N - 1)$ possible links for directed graphs and $\frac{N(N-1)}{2}$ for undirected graphs. (b) The measure of local interconnectivity between nodes is called clustering coefficient, (Δ_i denotes the clustering coefficient for node i and Δ is the coefficient for the network); (c) The shortest path length of the network estimates the average shortest path between all pairs of randomly selected nodes; and (d) Degree distribution which gives the probability distribution $P(k)$ of links of any number k , and $p(k)$ gives the probability that a randomly selected node has exactly k links. The average number of links per node is given by $\langle k \rangle = \sum_k kp(k)$ and the variance of links $\langle k^2 \rangle = \sum_k k^2 p(k)$. Where empirical sample data is used, $p(k) = \frac{N_k}{N-1}$ where N_k is the number of nodes with k links.

Clustering in networks measures how interconnected each agent's neighbours are and is considered to be the hallmark of social and species oriented networks. Specifically, there should be an increased probability that two of an agent's neighbours are also neighbours of one another. For each agent with k_i neighbours the total number of all possible directed links between them is given by $k_i(k_i - 1)$. Let E_i denote the actual number of links between agent i 's k_i neighbours, viz. those of i 's k_i neighbours who are also neighbours. The clustering coefficient Δ_i for agent i is given by

$$\Delta_i = \frac{E_i}{k_i(k_i - 1)} \text{ and } \Delta = \frac{\sum_{i=1}^N \Delta_i}{N}. \quad (3)$$

The second term which gives the clustering coefficient of the network as a whole is the average of all Δ_i 's. Note that the clustering coefficient for an Erdős-Renyi random graph is $\Delta^{random} = p$ where p is the same probability for any pair of nodes to be connected. This is because in a random graph the probability of node pairs being connected by edges are by definition independent, so there is no increase in the probability for two agents to be connected if they were neighbours of another agent than if they were not. A high clustering coefficient for the network corresponds to high local

interconnectedness of a number of agents in the core. In an Erdős-Renyi network, the degree distribution follows a Poisson distribution. In contrast, scale free networks have highly skewed distribution of links that follows a power law in the tails of the degree distribution, that is the probability of a node possessing k degrees is given by

$$p(k) = k^{-\alpha}, \quad (4)$$

where $\alpha > 0$ is called the power law exponent. Hence, there are some nodes which are very highly connected and many that are not. To generate power law statistics for nodes either in terms of their size or the numbers of links to/from them, Barabási and Albert (1999) proposed a process called preferential attachment, whereby nodes acquire size or numbers of links in proportion to their existing size or connectivity.

An important discovery that was made by Watts (1999) and Watts and Strogatz (1998) with regard to socio-economic networks is that while small world networks like scale free networks have in-egalitarian degree distribution with some very highly connected nodes, the central tiering of highly clustered nodes which work as hubs for the peripheral nodes (who have few direct connections to others in the periphery) is a signature feature only of small worlds. In order to get the core-periphery structure with a highly clustered central core, we follow the suggestion in Zhou and Mondragon (2003) and include the scope for preferential attachment or assortative mixing among the nodes with large number of outdegrees and not just a preference for high degree nodes (disassortative mixing) by low degree nodes. Note, the hubs also facilitate short path lengths between two peripheral nodes. We have indicated how such a tiered structure arise in broker-dealer structures as the hub members minimize liquidity and collateral costs by implementing offsets.

Finally, the statistic that will be used to characterize high concentration of activity, one which is closely related to the stability of the financial network is the eigenvector centrality statistic for the nodes characterizing CDS activity obtained for matrix Θ in (2). The algorithm that determines it assigns relative centrality scores to all nodes in the network based on the principle that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. Denoting v_i as the eigenvector centrality for the i th node, let the centrality score be proportional to the sum of the centrality scores of all nodes to which it is connected (ie. out degrees). Hence,

$$v_i = \frac{1}{\lambda} \sum_j \theta_{ij} v_j. \quad (5)$$

For the centrality measure, we take the largest real part of the dominant eigenvalue, λ_{max} , of matrix Θ in (2) and the associated eigenvector. The i^{th} component of this eigenvector then gives the centrality score of the i^{th} node in the network. Using vector notation for this, we obtain the eigenvector equation for matrix in (2) as:

$$\Theta \mathbf{v} = \lambda_{max}(\Theta) \mathbf{v}. \quad (6)$$

As the eigenvector of the largest eigenvalue of a non-negative real matrix Θ in (2) has only non-negative components, highly central nodes are guaranteed positive eigenvector values by Perron-Frobenius theorem (see, Meyer (2000), Chapter 8). Note, \mathbf{v} is the right eigenvector of the matrix Θ and will be shown to be the relevant centrality measure for the design of a super-spreader tax.

3.3. Economics Literature on Financial Networks

Pre 2007 financial network models in the economics literature have yielded mixed results. An influential and early work on connectivity in a financial network and that of financial contagion is that of Allen and Gale (2001). They gave rise to a mistaken view (see, Battiston et al. (2009)) that follows only in the case of homogenous graphs²⁰, ie. increasing connectivity monotonically increases system stability in the context of diversification of counterparty risk. A number of the analytical and numerically based studies in financial contagion work were confined to Erdős-Renyi random graphs such as Nier et al. (2007) and Gai and Kapadia (2010) which are interesting in terms of qualitative understanding one needs to get but as financial networks are far from random, they have some way to go.

As little empirical work has been done to date on network structures of the specific markets underpinning off-balance bank activity such as CDS

²⁰In a complete graph, if bank i 's total exposure is equally divided among its $N - 1$ counterparties, then risk is shared equally at the rate of $\frac{1}{N-1}$. The demise of a single counterparty has a very small impact on i . In contrast, Allen and Gale (2001) consider an incomplete circle network where each bank is exposed to only one other for the full 100% of its receivables, then the failure of any bank in the circle will bring the others down.

506 responsible for triggering and propagating the 2007 crisis, it must be noted
 507 that the bulk of the empirical financial network approach has been confined
 508 to interbank markets for their role in the spread of financial contagion (see,
 509 Furfine (2003) and Upper (2011)). However, the use of the entropy method²¹
 510 (see, Upper and Worms (2004) and Boss et al. (2004)) for the construction
 511 of the matrix of bilateral obligations of banks which results in a complete
 512 network structure for the system as a whole, greatly vitiates the potential
 513 for network instability or contagion. Recent work by Craig and von Peter
 514 (2010) using bilateral interbank data from German banks have identified the
 515 tiered core-periphery structure and find that bilateral flow matrix (X) in (1)
 516 unlike in a complete or as in a Erdős-Renyi random networks is sparse in the
 517 following way:

$$X = \begin{bmatrix} CC & CP \\ PC & PP \end{bmatrix}. \quad (7)$$

518 Here, CC stands for the financial flows among the core banks in the centre
 519 of the network, CP stands for those between core and periphery banks, PC
 520 between periphery and core banks and PP stand for flows between periphery
 521 banks. The sparseness of the matrix relates to the fact that PP flows are
 522 zero and banks in the periphery of the network do not interact with one an-
 523 other. This structure resembles the small world network described in Section
 524 3.1 above as being a characterization of *TITF* structure in the core of the
 525 network. Hence, the criticism Craig and von Peter level at extant financial
 526 networks literature is worth stating here. They say that many interbank mod-
 527 els proposed in the economics literature (e.g. Allen and Gale (2001), Freixas
 528 et al. (2000), and Leitner (2005)) ignore the tiered structure and do not anal-
 529 yse it in any rigorous way : “the notion that banks build yet another layer
 530 of intermediation between themselves goes largely unnoticed in the banking
 531 literature”. Craig and von Peter (2010) find that the tiered character of this
 532 market is highly persistent. This could coincide with an outcome of com-
 533 petitive co-evolution in that to retain status quo in market shares, the core
 534 banks are hugely geared to the arms race involved there (see, also Galbiati
 535 and Giansante (2010)). Craig and von Peter (2010) go on to note that “the

²¹For a recent criticism of the entropy method in the construction of networks, see, the
 2010 ECB Report on *Recent Advances in Modeling Systemic Risk Using Network Analysis*
 (ECB, 2010).

536 *persistence of this tiered structure poses a challenge to interbank theories that*
537 *build on Diamond and Dybvig (1983). If unexpected liquidity shocks were the*
538 *basis for interbank activity, should the observed linkages not be as random*
539 *as the shocks? Should the observed network not change unpredictably every*
540 *period? If this were the case, it would make little sense for central banks and*
541 *regulatory authorities to run interbank simulations gauging future contagion*
542 *risks. The stability of the observed interbank structure suggests otherwise.”*

543 From our experience of mapping the financial networks based on actual
544 bilateral data of FIs for the Indian financial system,²² there appears to be a
545 distinct variation in the core-periphery hierarchical structure noted by Craig
546 and von Peter (2010) in the different types of financial activities. In their
547 derivatives or contingent claims exposures and obligations, FIs show a far
548 more marked concentration in the core both in terms of financial flows and
549 connectivity, with a few banks in the core and a large number of them in
550 the periphery. In non-contingent claims based borrowing and lending the
551 interbank market shows more diffusion in the core with a larger number of
552 banks in the core. The least hierarchical is the RTGS payment and settle-
553 ments systems where there is a distinct lack of identifiable periphery banks.
554 That the credit based interbank markets have different network properties to
555 RTGS payment and settlement systems has also been noted by Kyriakopou-
556 los et al. (2009).²³ Their findings on the network topology of the Austrian
557 payment and settlement systems have been found to correspond to the study
558 of the Fedwire payment and settlement system by Soramaki et al. (2006).
559 Bech and Enghin (2008) did a detailed study of the network topology of
560 Fed Funds market and found that the clustering of the system was limited
561 and that small banks lend more to big banks than to their own sized banks
562 showing disassortative linkages. They found that this disassortativity was
563 reduced when links were weighted by value of flows. Hence, we emphasize
564 the need for empirical calibrations that reflect actual market concentration in
565 the financial activity or the use of full bilateral data on financial obligations
566 between counterparties.

567 Finally, the presence of highly connected and contagion causing players
568 typical of a clustered complex system network perspective is to be contrasted

²²See, Reserve Bank of India Financial Stability Report, December 2011.

²³Note, as shown in Kyriakopoulos et al. (2009) the network mapping of electronic real time payment and settlement systems is highly sensitive to the time scale over which flows are estimated. This problem is not something that has been resolved yet.

569 with what some economists regard to be an equilibrium network. Recently,
570 Babus (2009) states that in “an equilibrium network the degree of systemic
571 risk, defined as the probability that a contagion occurs conditional on one
572 bank failing, is significantly reduced”. Indeed, the premise of *TITF* is that
573 the failure of a highly connected bank will increase the failure of another
574 similarly bank, which we find to be the empirical characteristic of the network
575 topology of the CDS market involving US banks, indicates that the drivers
576 of network formation in the real world are different from those assumed in
577 economic equilibrium models.

578 Our analysis of the stability of highly clustered financial networks has
579 been influenced by the work of Robert May and studies on the spread of epi-
580 demics in non-homogenous networks with hierarchies (see, Kao (2010, p.62)).
581 May (1972, 1974) seminaly extended the Wigner condition of eigenvalues for
582 complete random matrices to sparse random networks. He was the first to
583 state that the stability of a dynamical network based system will depend on
584 the size of the maximum eigenvalue of the weighted adjacency matrix of the
585 network. Assuming the matrix entries are zero mean random variables, May
586 (1974) derives the maximum eigenvalue of the network, which we denote as
587 λ_{max} , in terms of three network parameters p , the probability of connectiv-
588 ity, N the number of nodes and σ which is the standard deviation of node
589 strength. The May (1974) result states that network instability follows when
590 $\sqrt{Np}\sigma > 1$. There is a trade off between heterogeneity in node strength, σ
591 and connectivity, p , in order for the network to remain stable. In a non-zero
592 mean random matrix, highly connected networks can remain stable only if
593 they are homogenous in node strength, viz. σ should be very small. In net-
594 works with high variance to mean ratio in degrees and with tiered hierarchies
595 of highly connected nodes where there is higher probability that a node is
596 connected to a highly connected one, the direction of the epidemic which
597 starts in a central hub follows a distinct hierarchical pattern with the highly
598 connected nodes being infected first and the epidemic then cascading toward
599 groups of nodes with smaller degrees, Kao (2010). Further, the epidemic
600 dies out at great speed once the super-spreaders are eliminated. In contrast,
601 in uncorrelated random graphs, the epidemic lasts longer and also reaches
602 more nodes. For epidemic control, clustered networks enable targeting of
603 specific individuals as opposed to inoculating the whole population in a ran-
604 dom graph. Sinha (2005) and Sinha and Sinha (2006), also find that while
605 both the small world and the Erdős-Renyi random graph show instability
606 according to the condition given by May (1974), the lack of structure in a

607 random graph results in a worse capacity of the system to cope with the
608 contagion.

609 In terms of propagation of failure, therefore and as it will be shown, it
610 is not true that financial systems where no node is too interconnected or
611 involved in a cluster (as in an Erdős-Renyi random network) are necessarily
612 easier to manage in terms of structural coherence and stability. Hence, we will
613 report on the stability analysis of the empirically calibrated US CDS network
614 and also of an equivalent random graph of the same size and functionality in
615 terms of the CDS fair value flows. The instability propagation in the highly
616 clustered empirically based CDS network and the equivalent random graph
617 is radically different and the less interconnected system is in some respects
618 more difficult to manage. This suggests the need for caution in espousing
619 an ideal network topology for financial networks. This also underscores the
620 importance of calibrations for networks in contagion analysis to be based
621 on actual financial flows for the market or some close empirical proxies for
622 network connectivity.

623 4. Contagion and Stability Analysis

624 The study of the topology of network in order to characterize its dy-
625 namical and stability properties has been actively studied especially in the
626 context of ecology of species and in epidemiology. In financial network model
627 the analysis of contagion from specific node failure has used the classic Furfine
628 (2003) methodology.

629 4.1. Furfine (2003) Methodology : Failure of A Single Trigger bank at Initial 630 Period

631 We follow the round by round or sequential algorithm for simulating con-
632 tagion that is now well known from Furfine (2003). Starting with a trigger
633 bank i that fails at time 0, we denote the set of banks that fail at each round
634 or iteration by D^q , $q = 1, 2, \dots$. Note, the superscript q shows the q^{th}
635 iteration. The cascade of defaults occur in the following way:

- i Assuming tear ups but no novation of CDS contracts and zero recovery rate on the trigger bank i 's liabilities, bank j fails if its direct bilateral net loss of CDS cover vis-à-vis the trigger bank i taken as a ratio of its capital (reported in the fifth column of Tables A.4, A.5 in the Appendix

A) is greater than a threshold ρ . That is,

$$\frac{(x_{ij} - x_{ji})^+}{C_j} > \rho.$$

636 This threshold ρ signifies a percentage of bank capital which can be re-
 637 garded as a sustainable loss. This is assumed to be the same for all
 638 banks.

- ii A second order effect of contagion follows if there is some bank $z, z \notin D^1$, ie. those that did not fail in round 1, suffers losses due to counterparty failure such that the losses are greater than or equal to a proportion ρ of its capital:

$$\frac{\left[(x_{iz} - x_{zi})^+ + \sum_{j \in D^1} (x_{jz} - x_{zj}) \right]}{C_z} > \rho.$$

639 The summation term aggregates the net loss of CDS cover to z from all
 640 banks $j, j \neq i$, which demised in the first iteration.

- iii This then iterates to the q^{th} round of defaults if there is some bank $v, v \notin D^1 \cup D^2 \dots \cup D^{q-1}$, ie. has not failed till $q - 1$, such that

$$\frac{\left[(x_{iv} - x_{vi})^+ + \sum_{j \in \bigcup_{s=1}^{q-1} D^s} (x_{jv} - x_{vj}) \right]}{C_v} > \rho.$$

- 641 iv The contagion is assumed to have ended at the round $q^\#$ when there are
 642 no more banks left or none of those that have survived fail at $q^\#$.

643 4.2. Network Stability Analysis

644 Using the matrix Θ in (2) whose entries give bilateral net liabilities of
 645 bank i to j as a ratio of bank j 's capital, in matrix notation the equations
 646 for the dynamics of the cascade of failure given the failure of the trigger
 647 bank can be given as follows. Consider the column vector \mathbf{U}_q with elements
 648 $(u_{1q}, u_{2q}, \dots, u_{nq})$ which give the probability of 'infecting' at the q th iteration.
 649 We have $u_{iq} = 1 = u_{iq}^1$ are those banks that fail at the q th iteration and infect
 650 all non-failed counterparties with probability 1. Those that fail prior to q
 651 have $u_{iq} = 0$, viz. they do not infect anybody. The non-failed banks at q
 652 have $0 < u_{iq} < 1$ and at $q + 1$ their probability of failure/infecting is given
 653 by :

$$\begin{aligned} \mathbf{U}_{iq+1} &= (1 - \rho)u_{iq} + \sum_j \frac{(x_{ji} - x_{ij})^+}{C_{i0}} u_{jq}^1 \\ &= (1 - \rho) \left(1 - \frac{C_{iq}}{C_{i0}}\right) + \sum_j \frac{(x_{ji} - x_{ij})^+}{C_{i0}} u_{jq}^1, \quad 0 < u_{iq+1} < 1. \end{aligned} \quad (8)$$

Here, in the first term in (8) ρ can be taken as the capital buffer for CDS assets, it can be considered to be equivalent to the rate of cure in the epidemic literature. Thus, $(1 - \rho)$ gives worst case rate of failure for a bank. It is convenient to assume the initial $u_{i0} = \frac{\rho}{(1-\rho)}$ while $u_{iq} = \left(1 - \frac{C_{iq}}{C_{i0}}\right)$. That is, the probability of failure is determined by the rate at which bank i 's capital is depleted by losses from failed banks. The second term in (8) sums up the infection rates sustained from its failed counterparties. Note, therefore, $u_{iq+1}^1 = 1$ or i fails at $q + 1$ when the R.H.S of (8) is greater than 1.

Thus, in matrix notation the dynamics of bank failures is given by:

$$\mathbf{U}_{q+1} = [\boldsymbol{\Theta}' + (1 - \rho)I] \mathbf{U}_q. \quad (9)$$

Here, $\boldsymbol{\Theta}'$ is the transpose of the matrix in (2) with each element $\Theta'_{ij} = \Theta_{ji}$ and I is the identity matrix. Recall the elements of the 2^{nd} row of $\boldsymbol{\Theta}'$ take the following form with for example, positive entries in (10) for counterparties 1, 3 and N and with $\Theta_{22} = 0$ to indicate that an FI does not 'infect' itself:

$$\boldsymbol{\Theta}'_{2t} = \left(\frac{x_{12} - x_{21}}{C_{20}}, 0, \frac{x_{32} - x_{23}}{C_{20}}, \dots, \frac{x_{N2} - x_{2N}}{C_{20}} \right). \quad (10)$$

The system stability of (9) will be evaluated on the basis of the power iteration of the initial matrix $\mathbf{Q} = [\boldsymbol{\Theta}' + (1 - \rho)I]$. From (9), \mathbf{U}_q takes the form:

$$\mathbf{U}_q = [\boldsymbol{\Theta}' + (1 - \rho)I]^q \mathbf{U}_0 = \mathbf{Q}^q \mathbf{U}_0. \quad (11)$$

It can be shown that the stability of the system is governed by the maximum eigenvalue of the initial matrix $\mathbf{Q} = [\boldsymbol{\Theta}' + (1 - \rho)I]$ when it satisfies the conditions:

$$\lambda_{max}(\mathbf{Q}) < 1. \quad (12)$$

$$\lambda_{max}(\Theta') < \rho. \quad (13)$$

674 Finally, $\lambda_{max}(\Theta') = \lambda_{max}(\Theta)$, that is the maximum eigenvalue of a real
 675 non-negative matrix is equal to that of its transpose. The Furfine (2003)
 676 contagion analysis highlights how a FI fails due to its exposures to the trigger
 677 bank, and hence as will be shown, the stabilization of the financial network
 678 system will exploit the role of row sums in Θ' as in a typical row given in
 679 (10). However, for purposes of managing systemic risk and the design of
 680 a super-spreader tax on a FI to have it internalize the cost to others from
 681 the excessive liabilities and connectivity that it has, we will use the right
 682 dominant eigenvector from matrix Θ which was defined in (6).

683 4.3. Super-spreader Tax

684 Financial systems determined by an initial matrix $\mathbf{Q} = [\Theta' + (1 - \rho)I]$
 685 in (9) that are prone to instability and contagion will have $\lambda_{max}(\mathbf{Q}) > 1$ and
 686 where pre-funded capital thresholds such as $\rho > 0$ apply, instability ensues at
 687 $\lambda_{max}(\Theta) > \rho$. There are 4 ways in which stability of the financial network can
 688 be achieved: (i) constrain the bilateral exposure of financial intermediaries;
 689 (ii) *ad hocly* increase the threshold ρ in (9,11); (iii) change the topology of
 690 the network (iv) Levy a capital surcharge or a capital buffer commensurate
 691 to the right eigenvector centrality of a FI in (6). The first two measures do
 692 not price in the negative externality from systemic risk associated with the
 693 failure of highly weighted network central nodes. Network topologies emerge
 694 endogenously and are hard to manipulate exogenously.

695 The aim of the super-spreader tax is to have financial intermediaries with
 696 high eigenvector centrality parameters to internalize the costs that they in-
 697 flict on others by their failure and to mitigate their impact on the system
 698 by reducing their contribution to network instability as given by $\lambda_{max}(\Theta')$.
 699 Hence, this can be considered to be a Pigovian tax.

700 Critical to the von-Mises power iteration algorithm (see Ralston (1965))
 701 for the calculation of $\lambda_{max}(\Theta')$ are the row sums S_i of the i^{th} row in Θ' ,

$$S_i = \sum_j \theta_{ji} = \frac{1}{C_i} \sum_j (x_{ji} - x_{ij})^+.^{24} \quad (14)$$

²⁴It should be noted that the upper bound of the maximum eigenvalue $\lambda_{max}(\Theta')$ is given by maximum of row sums of the matrix Θ' : $\lambda_{max} \leq \|\Theta'\|_\infty = \max_i \sum_j \Theta_{ji} = \max_i S_i$.

702 We create a new row sum $S_i^\#$, for each node so that a super-spreader
 703 tax denoted as $\tau(v_i)$ applies to the capital of the i^{th} node in proportion to
 704 its right eigenvector centrality v_i defined in (6):

$$S_i^\# = \sum_j \theta_{ji}^\# = \frac{1}{(1 + \tau(v_i)) C_i} \sum_j (x_{ji} - x_{ij})^+. \quad (15)$$

705 Thus,

$$S_i^\# < S_i \text{ for } \tau(v_i) > 0. \quad (16)$$

706 We set the super-spreader tax :

$$\tau(v_i) = \alpha v_i, \quad 0 < \alpha \leq 1 \text{ or } \alpha > 0. \quad (17)$$

707 The new matrix associated with $S_i^\#(\alpha)$, for all i , will be denoted as
 708 $\Theta'^\#(\alpha)$. The alpha parameter when set at 0 obtains the λ_{max} associated with
 709 the untaxed initial matrix Θ' . When $\alpha = 1$, each node is exactly penalized
 710 by v_i , which yields the λ_{max} for $\Theta'^\#(\alpha = 1)$. Considering, $0 < \alpha \leq 1$, there
 711 is a monotonic reduction in the λ_{max} associated with the matrices $\Theta'^\#(\alpha)$
 712 corresponding to the monotonic reduction in row sums $S_i^\#(\alpha = 1) < \dots <$
 713 $S_i^\#(\alpha = 0.75) < \dots < S_i^\#(\alpha = 0.5) < \dots < S_i(\alpha = 0)$. Clearly, the size of α ,
 714 in particular if $\alpha > 1$ is needed to stabilize the system, the sustainability of
 715 such a market for risk sharing is in question.

716 The nature of the systemic risk stabilization super-spreader fund is that
 717 it operates like an escrow fund. The super-spreader taxes that are collected
 718 aim to cover the losses that the most connected nodes will inflict on their di-
 719 rect ‘big’ neighbours in the first tier. The empirical section will demonstrate
 720 the extent to which a super-spreader tax has to be levied in order to stabi-
 721 lize the system. It is designed to work in a clustered hierarchical network
 722 where contagion takes a specific pathway amongst the central tier if a highly
 723 connected node fails. In fact, often reducing λ_{max} to a desired level may not
 724 be technically feasible and may involve exorbitant levels of tax. Instead, we
 725 aim to secure a super-spreader *lite* escrow fund which will escrow sufficient

Here, $\|\cdot\|_\infty$ infinity norm of a matrix is the maximum of row sums S_i where $S_i = \sum_j \Theta_{ji}$. Hence, high connectivity to large number of counterparties and also large exposures relative to capital contribute to the high row sums for FIs and with the largest of these being the upper bound of $\lambda_{max}(\Theta')$. For a more detailed discussion of this and how stabilization using alternative applications of the right eigenvector centrality of FIs, see Markose (2012).

726 funds to cover the largest amount of first round losses from the failure of the
727 dominant bank in terms of eigenvector centrality.

728 5. Empirical Results

729 5.1. Empirical (Small World) Network Algorithm

730 We study the US banks involved in the CDS market as recorded in the
731 FDIC Call Reports for 2007 and 2008 Q4. In order to exclusively focus on the
732 systemic risk from potential counterparty risk leading to loss of cover from
733 CDS, FDIC data is obtained for CDS gross notional (buy and sell), Gross
734 positive fair value (GNFV), Gross negative fair value (GNFV) and Tier 1
735 capital. Tables A.4, A.5 in the Appendix A report the key data for 2007
736 and 2008 Q4.

737 As discussed, we use an algorithm that assigns network links on the basis
738 of market shares (see, Tables A.4, A.5 in Appendix A) in order to reflect the
739 very high concentration of network connections among the top 6 banks in
740 terms of bilateral interrelationships. We first construct the X matrix given
741 in (1). Our algorithm assigns in degrees and out degrees for a bank in terms
742 of its respective market shares for gross notional values for CDS purchases
743 and sales. Thus, in 2007 Q4 J.P. Morgan with a 50% share on both sides
744 of the market will approximately have 15 in and out degrees. The choice of
745 these 15 banks J.P. Morgan has out degrees to is assortative, i.e. 15 banks
746 are chosen from the largest to the smallest in terms of their CDS activity.

- 747 • S_i^G : $Bank_i$ market share in terms of the gross notional on the sell side
748 of CDS
- 749 • S_i^B : $Bank_i$ market share in terms of the gross notional on the buy side
750 of CDS
- 751 • G_i : Gross Negative Fair Value for which $Bank_i$ is a guarantor vis-à-vis
752 its counterparties
- 753 • B_i : Gross Positive Fair Value for which $Bank_i$ is beneficiary vis-à-vis
754 its counterparties

755 The algorithm then allocates to each row bank i 's counterparties j , a value
756 of i 's GNFV equal to $S_j^B G_i$ and if $\sum_j S_j^B G_i < G_i$, then bank i allocates the
757 remaining to the external non-US bank entity which is the $N + 1$ agent. The

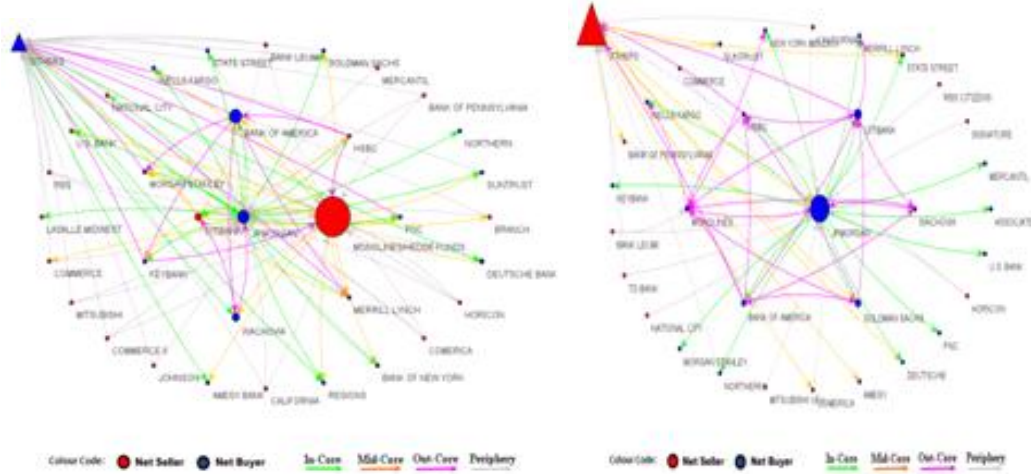


Figure 3: The Empirically Constructed CDS Network (Bilaterally Netted) for US Banks and Non-US Financial Intermediaries (Triangle): Empirical Small World Network in Tiered Layout (LHS 2007 Q4 and RHS 2008 Q4).

row sums of matrix X in (1) are made to satisfy the $GPFV_j$ or B_j for each bank, the following allocation rule is used such that if $S_j^B \sum_i G_i < B_j$, the remaining is bought from the external entity.

In order to determine each bank's share of GNFBV to the US non-bank sector which includes Monolines and hedge funds we use data from Table RCL-16a, "Derivatives and Off-Balance Sheet Items", from FDIC Call Reports which gives a sectoral break down. Finally, the share of a bank's GNFBV for the entity called 'others' which denotes non-US counterparties is obtained as a balancing item to satisfy the condition given in (1) that $\sum_i G_i = \sum_j B_j$. The gross flow X matrix so constructed using the above algorithm is a sparse matrix with a very high concentration of activity. We then derive the bilaterally netted exposures between a pair of banks which can be read off accordingly as $(x_{ij} - x_{ji})$ with x_{ij} denoting GNFBV for CDS protection from i to j and x_{ji} is GNFBV protection cover from j to i . Hence, the size of bilateral net sell amount is given by $(x_{ij} - x_{ji}) > 0$. The resulting network for this is graphed below in Figure 3.

In Figure 3, red nodes denote net CDS sellers and blue nodes are net CDS buyers. The main difference between the US CDS networks for 2007 Q4 and 2008 Q4 is that the dominant role of the Monolines and hedge funds as net CDS sellers (largest red coloured node, LHS) has almost all been phased out

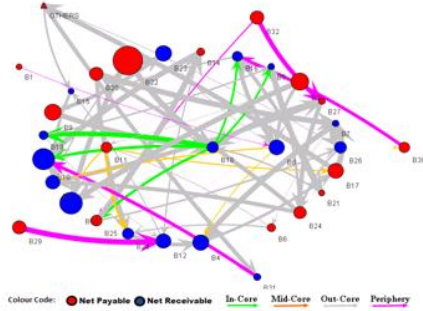


Figure 4: Erdős-Renyi Random Graph (Equivalent to 2008 Q4 CDS Network in Figure 3 RHS) for US Banks and Non US Sector (Triangle): Absence of an identifiable core-periphery structure

by the end of 2008. By 2008 Q4 J.P. Morgan has increased its dominance as the sole member of the inner core and non-US banks (red triangle) become net protection providers. Hence, there are clear threats from the non-US sector, viz. European banks, which we will briefly analyse. The other top 5 US banks remain in the central core of the network in somewhat weaker positions with the exception of Goldman Sachs which migrates more to the centre in 2008 Q4. Over 80% of the banks are in the periphery with almost no connectivity among themselves manifesting a very sparse adjacency matrix.

The tiered layout in Figure 3 is constructed in the following way. We take the range of connectivity of all banks as a ratio of each bank's total in and out degrees divided by that of the most connected bank. Banks that are ranked in the top 20 percentile of this ratio constitute the inner core. This is followed by a mid core between 80 and 50 percentile and a 3rd tier between 10 and 50 percentile. Those with connectivity ratio less than 10 percentile are categorized as the periphery.

The links are weighted and thicker the links, the larger the size of their obligations. The links are colour coded. The triangle entity representing non-US banks constitutes the mid-core. So the yellow links show where the second tier (mid core) banks are offering protection. As can be seen, the banks with the pink arrows in the core almost always interact with one another.

Table 1 gives the network statistics for the empirically constructed CDS networks and also for the equivalent random graph representing the 2008 CDS data given in Figure 4. The random graph is constructed with the same connectivity of about 6% as the market share based empirically con-

Initial Network Statistics	Mean	Standard Deviation (σ)	Skewness	Kurtosis	Connectivity	Clustering Coefficient	$\langle k^2 \rangle / \langle k \rangle$: Variance to Mean Ratio
2008 Q4 In Degrees CDS Buyers	1.94	2.95	3.27	12	0.06	0.619	4.48
2008 Q4 Out Degrees CDS Sellers	1.94	3.07	3.41	14.12			4.85
2007 Q4 In Degrees CDS Buyers	2.97	5.29	3.48	13.481	0.087	0.35	9.42
2007 Q4 Out Degrees CDS Sellers	2.97	3.80	3.09	9.86			4.86
2008 Q4 Random Graph In Degrees	1.91	1.13	-0.089	-0.752	0.059	0.107	0.648
2008 Q4 Random Graph Out Degrees	1.91	1.13	1.161	2.21			0.648

Table 1: Network Statistics for Degree Distribution for CDS Network: Small World Network Properties Compared with Random Graph with Same Connectivity

802 structured network for 2008 Q4 (see, Appendix B for the algorithm used in
803 the construction of the random graph.) The main difference in the network
804 statistics for the 2007 Q4 and 2008 Q4 CDS networks is the jump in the
805 clustering coefficient in 2008 Q4 to 62% from 35% while connectivity has
806 fallen from about 8% to 6%. The random graph has a much lower cluster
807 coefficient of 10% compared to that of about 62% for the empirical CDS net-
808 work based on the 2008 Q4 data. Also, the random graph has substantially
809 low variance to mean ratio than the empirically calibrated CDS networks.
810 The highly asymmetric nature of the empirical CDS network is manifested
811 in the large kurtosis or fat tails in degree distribution which is characterized
812 by a few (two banks in this case) which have a relatively large number of in
813 degrees (up to 14) while many have only a few (as little as 1).

814 5.2. Eigenvector Centrality and Furfine Stress Test Results

815 Here we will investigate the idea about the role of super-spreaders of con-
816 tagion in terms of their network connectivity, dominance as CDS protection
817 sellers and their right eigenvector centrality. As already noted, in the post
818 Lehman era of 2008 Q4, the dominance of J.P. Morgan is the key aspect of

Trigger Bank (1)	Share of out (in) degrees	Weighted Eigenvector Centrality	Loss to Tier 1 Capital at q=1 (%) *Not Including that of Trigger Bank	Number of Banks Failed Not Including the Trigger Bank
JP Morgan	0.5 (0.48)	0.749	\$55.19 bn* (11.49%)	8 including Monolines
Goldman Sachs	0.093 (0.094)	0.1097	\$14.55bn*(2.87%)	2 including Monolines
HSBC	0.093(0.094)	0.0302	\$4.53bn* (0.89%)	Only Monolines
Citibank	0.125(0.125)	0.0862	\$0.43bn (0.000%)	0
Bank of America	0.156(0.0625)	0.0622	6.82 (1.34%)	2 including Monolines
Morgan Stanley	0 (0.03125)	0		
Merrill Lynch	0(0.0625)	0		
Monolines	0.125(0.156)	0.069		0
Others		0.6436		

Table 2: 2008 Q4 Eigenvector Centrality and Furfine Stress Tests (for selected banks) with 6% capital threshold.

819 the US sector of the CDS market. Table 2 shows that in terms of connectiv-
 820 ity, J.P. Morgan stands out by a large margin with 55% share of total out
 821 degrees. Citibank has 12.5% of outdegrees while Goldman Sachs and HSBC
 822 come in at third place with a modest 9.3% share. In terms of eigenvector
 823 centrality which correlates best with contagion losses the trigger bank inflicts
 824 on others, again J.P. Morgan has eigenvector centrality of 0.749 followed by
 825 *Others* at 0.64 and Goldman Sachs and Citibank at 0.1 and 0.086 respec-
 826 tively. This is borne out in the Furfine stress tests results given in Table 2
 827 and Figure 5. Over all, J.P. Morgan as trigger bank results in the failure
 828 of Morgan Stanley, Citibank, Bank of America, Goldman Sachs, HSBC and
 829 Merrill Lynch in the first tier of the network. This results in \$55.19 bn loss
 830 of Tier 1 Capital to the direct counterparties of J.P. Morgan. One of our ob-
 831 jectives is to see if the super-spreader tax escrow fund can raise this amount
 832 of funds.

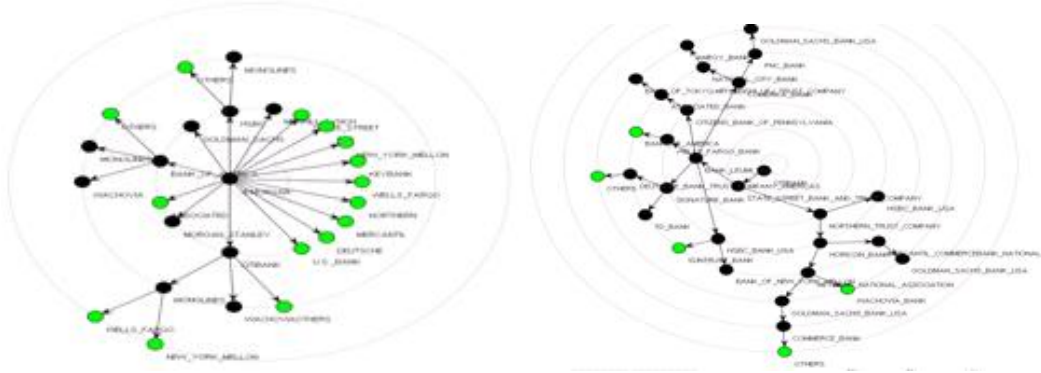


Figure 5: Instability propagation in Clustered CDS Network(2008 Q4 LHS) and in Equivalent Random Network (RHS) NB: Concentric circles mark the iterations q given in section 4.1; failed banks are black nodes and green nodes are those that are ‘hit’ but do not fail.

5.3. Contagion: Clustered Small World vs Random CDS Network

For the 2008 Q4 period, we will compare the CDS network stability of a random graph of the same size, connectivity and gross flow functionalities with that of the more clustered empirically based CDS network. Some very interesting issues, discussed in Section 4, are highlighted here. Recall the marked difference in structure is the clustering coefficient of the two networks and high variance to mean ratios (see, Table 1). The high clustering of the small world network in regard of what we understand to be the most likely structure for the CDS network in order to reflect the high concentration of exposures between 5 or so counterparties, results in a similar pattern in the propagation of financial contagion from the demise of the dominant bank, J.P. Morgan. As shown in Figure 5 (LHS) in the clustered network, there are only direct failures in a closed sector rather than higher order failures spreading to the whole system. It is, ofcourse, cold comfort that the first order shock wipes out the top 5 banks. Together they lead to the failure of the non-bank US CDS users. In contrast, in the random graph, while no node is either too big or too interconnected, the substantial part of the system unravels (up to 25 banks fail) in a series of multiple knock on effects. Note the concentric circles denote the sequence of cascade or iteration q described in section 4.1. The black nodes are the failed banks and the green ones are those that are hit but do not fail.

5.4. Quantification and Evaluation of the Super-spreader Tax (2008 Q4)

With a maximum eigenvalue of 1.18 for the Θ matrix in 2008 Q4, the system is deemed unstable and the losses to the system as a whole from the failure of the eigenvector dominant bank, J.P. Morgan, remains substantial with the failure of 5 top banks (see Figure 5 LHS). Socialized losses have to be internalized by the banks themselves. In this section, we will evaluate the super-spreader tax based on the theoretical derivation in Section 4.3 and equation (17). A surcharge on bank capital commensurate to the eigenvector centrality of a bank using the formula in equation (17) $\tau(v_i) = \alpha v_i$ is applied to the rows of Θ' for different values of $0 < \alpha \leq 1$. Note the eigenvector centrality for the top 5 US banks, Monolines and *Others* is given in Table 2. Compared to the target maximum eigenvalue of 1.06, the application of the capital surcharge in (17) to the matrix Θ' results in some small reduction in λ_{max} .

Figure 6 gives the rate of super-spreader capital surcharge that needs to be levied on the banks in order that they internalize the systemic risk costs arising solely from their network centrality. The super-spreader tax rate is obtained by multiplying the eigenvector centrality of each node v_i by the alpha parameter given in equation (17) which can then reduce the λ_{max} of the matrix Θ' . Table 3 will focus on the case of $\alpha = 0.125$ for which we find that the super-spreader escrow fund can stabilize the system. It is important to see if the super-spreader escrow fund can obtain sufficient funds which can cover the Tier 1 capital losses sustained (approximately \$67 bn in the absence of any pre-existing threshold and \$55 bn if a 6% threshold exists) when the most eigenvector dominant bank J.P. Morgan fails. What is clear from the analyses is that in the post Lehman period, the systemically important players in the US sector of the CDS market are J.P. Morgan and the non-US European banks taken in aggregate form as *Others*. The bulk of the Pigovian taxes fall on these two entities and only four other US banks need to be levied a non-zero tax on the basis of their network centrality parameter to fully price in the potential threat to the tax payer if they fail. As shown in Figure 6 and Table 3, J.P. Morgan's capital surcharge stands at about 9.37%, 8.04% for the non-US banks (*Others*), 1.372% for Goldman Sachs, 0.37% for HSBC, 1.077% for Citibank and 0.77% for Bank of America. Table 3 gives the amounts that will accrue in the super-spreader fund and we verify that this will cover over \$ 55.19 bn losses that will be incurred by the demise of the 5 top tier banks due to the failure of the dominant eigenvector central bank, J.P. Morgan.

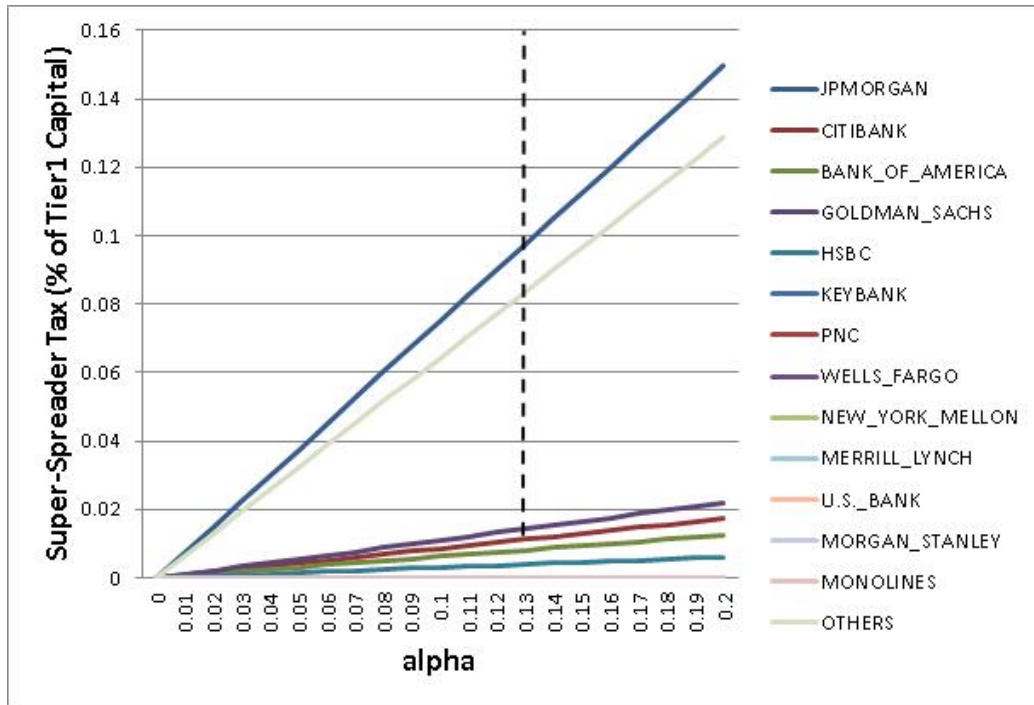


Figure 6: Super-spreader Tax Rates On Banks and Alpha (Equation 17) to Achieve Different Levels of Network Stability (Vertical line shows the tax rates and alpha necessary to secure the super-spreader lite funds necessary to \$55.19 bn 1st round losses of dominant eigenvector central bank.

Banks	Eigen Vector Centralit y	Tier 1 Capital	Super Spreader Tax Rate (alpha=0 .125)	Super Spreader Tax \$bns (alpha=0 .125)	\$bns Loss Round 1; r= 0	\$bns Loss above r= 0.06
JP Morga	0.7494	100.597	9.37%	9.42325		
Citibank	0.0862	70.977	1.08%	0.76434	33.12	2.86
Bank of A	0.0622	88.97902	0.78%	0.69214	19.69	14.35
Goldman	0.1097	13.212	1.37%	0.18117	8.91	8.118
HSBC	0.0302	10.82192	0.38%	0.04087	2.75	2.099
Keybank	0	8.012102	0.00%	0	0.026	
PNC	0	8.337592	0.00%	0	0.19	
Wells Fa	0	33.129	0.00%	0	0.066	
Merill L	0	4.321213	0.00%	0	0.966	
U.S. Banl	0	14.55817	0.00%	0	0.0056	
Morgan S	0	5.776	0.00%	0	0.0056	1.75
OTHERS	0.6436	544.383	8.05%	43.79339		
TOTAL				54.8952	67.988	55.187

Table 3: Super-spreader Tax Escrow Fund (Total and selected banks) and Value of Round 1 Tier 1 Capital Losses (Super-spreader Tax (\$bns) calculated by multiplying Tier1 capital by the tax rate (%)).

892 6. Concluding Remarks

893 This paper investigated the systemic risk posed by the topological fragility
894 of the CDS market due to the concentration in CDS exposures between few
895 highly connected US banks. To date, till the work of Craig and von Peter
896 (2010), financial network modellers have failed to sufficiently focus on the
897 core-periphery structure of financial intermediaries. A large number of fi-
898 nancial network models have either assumed a Erdős-Renyi random network
899 structure (see, Nier et al. (2007)) or that of a complete graph constructed by
900 entropy methods. The entropy based models are known not to produce fi-
901 nancial contagion with the failure of any trigger bank (see, Upper and Worms
902 (2004)). The core-periphery tiered network is particularly relevant for deriva-
903 tives markets. The framework we use to build an empirically based network
904 for the CDS obligations primarily between US banks and an aggregated non-
905 US sector reveals the high clustering phenomena of small world networks
906 along with a sparse adjacency matrix. We used the market share of CDS
907 activity by banks to determine the network structures as discussed above.

908 We have characterized *TITF* phenomena of the CDS market with the
909 tiered structure given in Figure 3. The 2008 Q4 CDS network is seen to
910 have substantially more clustering than in 2007 Q4 and gives evidence of the
911 greater concentration of CDS exposures among even fewer US banks than
912 in 2007. The threat to the US sector of the CDS market primarily from
913 the European banks has been identified in the post Lehman period. The
914 clustered network as seen in Figure 4 showed the radically different way in
915 which contagion propagates in contrast with an Erdős-Renyi network. This
916 is well understood in network models of epidemics, but not so much in finan-
917 cial models. Clustered small world network structure has some capacity for
918 containment of contagion and in complex system terms these highly intercon-
919 nected multi-hub based systems can have some stabilizing effects compared to
920 the unstructured random graphs. However, it is clear that the increased ca-
921 pacity to bear the first order shocks by the hub entities could only be achieved
922 by installing ‘super-spreader reserves’, overturning the current practice of le-
923 niency in this direction.

924 The financial network implied by the bilateral exposures given in a matrix
925 such as Θ' in section 4 is examined for its stability in terms of its maximum
926 eigenvalue. We found the empirically calibrated CDS network for the bilat-
927 erally netted exposures for the US FDIC banks for 2008 Q4 has maximum
928 eigenvalue of about 1.18. The network shows that J.P. Morgan is the most

929 dominant bank in regard to eigenvector centrality, followed closely by the
 930 European banks and then only by a long margin by other US banks such
 931 as Goldman Sachs and Citibank. In order for banks to internalize the sys-
 932 temic risk from their high network centrality, we recommend that banks be
 933 taxed by a progressive tax rate based on their eigenvector centrality and to
 934 escrow these funds. This is the first operationalization of this concept with
 935 the application of the super-spreader tax demonstrated to better stabilize
 936 the matrix of netted liabilities of financial intermediaries. We ‘back tested’
 937 the capacity of this fund to cover the maximum losses from the failure of the
 938 most network central bank. The stability analysis is one that can be used to
 939 evaluate the adequacy of the amounts of collateral or capital to absorb losses
 940 from a potential failure of counterparties even in a Central Clearing Platform
 941 without tax payer bailouts. Further experimentation with a multi-agent fi-
 942 nancial network model is needed to answer questions such as: how well will
 943 the super-spreader tax fund perform, one which is based only on unweighted
 944 eigenvector centrality of the financial intermediaries which requires much less
 945 information ? How will banks change their behaviour when faced by the full
 946 cost of being *TITF*? Can the super-spreader tax be applied and altered like
 947 traffic congestion pricing scheme as the behaviour of agents adapt to the
 948 regulatory changes (see Markose et al. (2007))?

949 It is our view that the size of derivatives markets and CDS markets, in
 950 particular, far exceed their capacity to internalize the potential losses that
 951 follow from the failure of highly connected financial intermediaries. The large
 952 negative externalities that arise from a lack of robustness of the CDS financial
 953 network from the demise of a big CDS seller further undermines the justifi-
 954 cation in Basel II and III that banks be permitted to reduce capital on assets
 955 that have CDS guarantees. We recommend that the Basel II provision for
 956 capital reduction on bank assets that have CDS cover should be discontin-
 957 ued. Banks should be left free to seek unfunded CDS cover for bank assets
 958 without the incentive of capital reduction and leverage. Indeed, this may
 959 enhance price discovery role of the CDS market relating to the probability
 960 of default of reference assets or entities.

961 **Appendix A. FDIC Data**

Name	Gross Notional CDS Buy		Gross Notional CDS Sell		GPFV		GNFV		Tier 1 Core Capital
JPMORGAN	4016.58	51%	3860.57	50%	130.19	44%	126.08	44%	78.45
BANK OF AMERICA	1483.96	19%	1522.46	20%	55.88	19%	51.25	18%	75.40
CITIBANK	1610.32	20%	1505.62	19%	76.59	26%	78.08	27%	81.95
HSBC	586.65	7%	638.07	8%	19.71	7%	19.79	7%	9.70
WACHOVIA	179.63	2%	188.35	2%	14.53	5%	12.65	4%	40.47
KEYBANK	4.35	0%	3.33	0%	0.07	0%	0.06	0%	7.14
PNC	3.96	0%	2.10	0%	0.10	0%	0.06	0%	7.85
WELLS FARGO	1.88	0%	0.87	0%	0.08	0%	0.03	0%	29.55
NATIONAL CITY	1.38	0%	0.85	0%	0.01	0%	0.01	0%	8.36
SUNTRUST	0.78	0%	0.31	0%	0.02	0%	0.02	0%	12.34
MITSUBISHI UFJ	0.01	0%	0.15	0%	0.00	0%	0.02	0%	0.78
REGIONS	0.07	0%	0.13	0%	0.01	0%	0.00	0%	9.80
COMMERCE BRANCH BANKING AND TRUST	0.00	0%	0.07	0%	0.00	0%	0.00	0%	2.49
COMMERCE	0.00	0%	0.03	0%	0.00	0%	0.00	0%	1.15
RBS	0.00	0%	0.02	0%	0.00	0%	0.00	0%	7.93
CITIZENS BANK LEUMI	0.00	0%	0.01	0%	0.00	0%	0.00	0%	0.42
JOHNSON	0.00	0%	0.01	0%	0.00	0%	0.00	0%	0.31
COMERICA	0.01	0%	0.01	0%	0.00	0%	0.01	0%	5.73
HORICON	0.00	0%	0.01	0%	0.00	0%	0.00	0%	0.04
CITIZENS BANK OF PENNSYLVANIA	0.00	0%	0.00	0%	0.00	0%	0.00	0%	2.26
BANK OF NEW YORK	2.09	0%	0.00	0%	0.04	0%	0.00	0%	6.46
CALIFORNIA BANK & TRUST	0.00	0%	0.00	0%	0.00	0%	0.00	0%	0.69
AMEGY BANK	0.00	0%	0.00	0%	0.00	0%	0.00	0%	0.74
MORGAN STANLEY	15.32	0%	0.00	0%	0.27	0%	0.03	0%	3.15
DEUTSCHE BANK	0.10	0%	0.00	0%	0.38	0%	0.02	0%	8.49
MERCANTIL COMMERCE BANK	0.01	0%	0.00	0%	0.00	0%	0.00	0%	0.44
STATE STREET BANK	0.24	0%	0.00	0%	0.00	0%	0.00	0%	6.91
U.S. BANK	0.06	0%	0.00	0%	0.00	0%	0.00	0%	13.21
GOLDMAN SACHS	0.56	0%	0.00	0%	0.01	0%	0.00	0%	1.21
MERRILL LYNCH	8.73	0%	0.00	0%	0.23	0%	0.01	0%	6.51
NORTHERN TRUST	0.28	0%	0.00	0%	0.00	0%	0.00	0%	3.02
LASALLE BANK MIDWEST	2.10	0%	0.00	0%	0.00	0%	0.00	0%	2.05
AGGREGATE	7919.07		7723.03		298.11		288.13		443.48

Table A.4: FDIC Data (2007 Q4) for 33 US Banks With CDS Positions (\$ bn)

Name	Gross Notional CDS Buy		Gross Notional CDS Sell		GPFV		GNFV		Tier 1 Core Capital
JP Morgan Chase	4166.76	53%	4199.10	54.3%	538.87	48%	455.56	46%	100.61
Citibank	1397.55	18%	1290.31	16.7%	211.65	19%	188.43	19%	70.98
Bank of America	1028.65	13%	1004.74	13.0%	132.04	12%	123.75	13%	88.50
Goldman Sachs	651.35	8%	614.40	7.9%	144.67	13%	131.75	13%	13.19
HSBC	457.09	6%	473.63	6.1%	64.83	6%	64.49	7%	10.81
Wachovia	150.75	2%	141.96	1.8%	24.08	2%	23.35	2%	32.71
Morgan Stanley	22.06	0%	0.00	0.0%	2.13	0%	0.03	0%	5.80
Merrill Lynch	8.90	0%	0.00	0.0%	1.19	0%	0.02	0%	4.09
Keybank	3.88	0%	3.31	0.0%	0.19	0%	0.17	0%	8.00
PNC	2.00	0%	1.05	0.0%	0.29	0%	0.09	0%	8.34
National City	1.29	0%	0.94	0.0%	0.00	0%	0.01	0%	12.05
The Bank of NY Mellon	1.18	0%	0.00	0.0%	0.08	0%	0.00	0%	11.15
Wells Fargo	1.04	0%	0.49	0.0%	0.15	0%	0.08	0%	33.07
SunTrust	0.59	0%	0.20	0.0%	0.26	0%	0.24	0%	12.56
The Northern Trust Company	0.24	0%	0.00	0.0%	0.04	0%	0.00	0%	4.39
State Street Bank and Trust Company	0.15	0%	0.00	0.0%	0.11	0%	0.00	0%	13.42
Deutsche Bank Trust Company Americas	0.10	0%	0.00	0.0%	0.00	0%	0.00	0%	7.87
Regions Bank	0.08	0%	0.41	0.0%	0.00	0%		0%	9.64
U.S. Bank	0.06	0%	0.00	0.0%	0.01	0%	0.00	0%	14.56
Commerce Bank	0.02	0%	0.03	0.0%	0.00	0%	0.00	0%	1.37
Mercantil Commercebank	0.01	0%	0.00	0.0%	0.00	0%	0.00	0%	0.54
Associated Bank	0.01	0%	0.12	0.0%	0.00	0%	0.00	0%	1.58
Comerica Bank	0.01	0%	0.05	0.0%	0.01	0%	0.03	0%	5.66
Signature Bank	0.00	0%	0.00	0.0%	0.00	0%	0.00	0%	0.76
RBS Citizen	0.00	0%	0.06	0.0%	0.00	0%	0.00	0%	8.47
Bank of Tokyo-MF	0.00	0%	0.05	0.0%	0.00	0%	0.04	0%	0.70
Aggregate	7893.77		7730.85		1120.60		988.04		480.82

Table A.5: FDIC Data (2008 Q4) for 27 US Banks With CDS Positions (\$ bn)

962 Appendix B. Random Network Algorithm

963 The algorithm that creates a random network of CDS obligations proceeds
964 on the following steps:

- 965 1. An adjacency matrix $\mathbf{A}(N \times N)$ is created where each element has
966 value 1 with probability p (this probability is set to be equal to the
967 connectivity of the empirical network we want to compare with), 0
968 otherwise.
- 969 2. A matrix $\mathbf{R}(N \times N)$ of random numbers is created where each element
970 r_{ij} is randomly drawn from a uniform distribution in the range $[0, 1]$.
- 971 3. The matrix $\mathbf{B}(N \times N)$ of random values is generated as follows: $B =$
972 $A * R$ (element by element multiplication). The matrix \mathbf{B} is now a sparse
973 matrix with many zero elements.
4. The final flow matrix corresponding to X in equation (1) of CDS obli-
gations \mathbf{X} is defined as

$$\mathbf{X} = \mathbf{B} \frac{\Gamma}{\sum_i \sum_j b_{ij}}.$$

974 Here, Γ is the total CDS GNFBV in the market as required by the
975 empirically constructed matrix

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